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A study is underway to investigate relationships of water depth, bottom type, and other optical variables to upwelling spectral radiance of coastal waters. A neural network and data from the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) are used to quantify these relationships. Data is analyzed for two areas: one on the western coast of Florida in Tampa Bay and the other on the Florida panhandle in Santa Rosa Sound. AVIRIS data from Tampa Bay is atmospherically corrected, whereas the data from the Santa Rosa Sound is not atmospherically corrected. The neural network can compute reasonable depths from spectral radiance in both cases. Sounding data obtained from the National Ocean Survey (NOS) hydrographic database is used in the training phase of the neural network and to test the accuracy of the result. Depths estimated by the neural network for Tampa Bay are accurate to a RMS error of 3.9 ft and for the Santa Rosa Sound to 3.0 ft. A crude bottom type classification of unknown accuracy emerged as a by-product of the investigation.

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bathymetry, spectral radiance, coastal water, neural network, AVIRIS, Tampa Bay, Santa Rosa Sound, and hydrographic database

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# COASTAL BATHYMETRY FROM HYPERSPECTRAL DATA

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## ABSTRACT

A study is underway to investigate relationships of water depth, bottom type, and other optical variables to upwelling spectral radiance of coastal waters. A neural network and data from the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) are used to quantify these relationships. Data is analyzed for two areas: one on the western coast of Florida in Tampa Bay and the other on the Florida panhandle in Santa Rosa Sound. AVIRIS data from Tampa Bay is atmospherically corrected, whereas the data from the Santa Rosa Sound is not atmospherically corrected. The neural network can compute reasonable depths from spectral radiance in both cases. Sounding data obtained from the National Ocean Survey (NOS) hydrographic database is used in the training phase of the neural network and to test the accuracy of the result. Depths estimated by the neural network for Tampa Bay are accurate to a RMS error of 3.9 ft and for the Santa Rosa Sound to 3.0 ft. A crude bottom type classification of unknown accuracy emerged as a by-product of the investigation.

## 1. INTRODUCTION

In recent years, the Navy emphasis in oceanography has shifted from deep ocean investigation to shallow water problems. With this advent, remote sensing instruments with higher spatial and spectral resolution are needed. AVIRIS, an Earth-observing imaging spectrometer sponsored by the National Aeronautics and Space Administration (NASA) and designed, built, and operated by the Jet Propulsion Laboratory (JPL), is well suited to this task. AVIRIS measures total upwelling radiance over the .4 to 2.4 $\mu$m spectral range in 224 channels spaced at 10 nm intervals (Figure 1). Images are about 11 km wide by up to 100 km in length with 20- by 20- nm spatial resolution[1,2]. AVIRIS data were initially used in geology, vegetation studies, ecology, and other land-based remote sensing applications. An ongoing series of sensor improvements in signal-to-noise ratio have made AVIRIS increasingly attractive for coastal oceanography. This investigation applies AVIRIS data to the problem of coastal bathymetry. The approach involves neural networks to estimate water depth from the upwelling spectral radiance data recorded by AVIRIS.

## 2. OBJECTIVE

This study was undertaken to investigate the use of neural networks to estimate coastal bathymetry. A neural network is a parallel computing architecture that can be trained by supervised learning to perform non-linear mappings, such as the mapping from spectral radiance to water depth. The neural network used in this study is a feed-forward, fully connected net with an input layer, two hidden layers, and an output layer. Supervised training is accomplished by back-propagation, which iteratively presents spectral data as input and NOS depth as the corresponding desired output. Back propagation uses a gradient descent search technique to adjust network parameters at each iteration to minimize the mean squared error between the desired output and the actual network output. The training should result in a network that produces least-squares estimates of depth given input spectra from the training set. The trained network is tested with an independent set of input data not included in the training process. Accuracy statistics cited in this paper are for these independent test sets. If the neural network can learn a mapping from spectral signature to water depth with sufficient accuracy to be useful in practical

applications, the objective of this study will be met. A secondary objective is to determine how universal these mappings might be. The secondary objective is touched upon here but more work is required for definitive answers.

## 3. APPROACH

AVIRIS data used in this study was collected on the western coast of Florida around Tampa Bay (Figure 2) and in Santa Rosa Sound in the Florida panhandle (Figure 3). The data for Tampa Bay was radiometrically calibrated and atmospherically corrected by JPL. The data for the Santa Rosa Sound is raw data, not atmospherically corrected. Since the upwelled energy from the oceanic water column is primarily limited to the visible part of the spectrum (Figure 1), only the first forty AVIRIS channels were originally chosen for use in this study. The analysis showed that channel 1 is all zeroes and channel 2 is very noisy, so channels 3-41 became the final band selection.

The ground truth data used in this study are soundings from the NOS hydrographic database. For the Tampa Bay area, there are 6712 bathymetry measurements in the area of interest. The training set contains 6444 samples, and the independent test set has 268 samples. The Santa Rosa Sound study area contains 336 bathymetry measurements, which is not large enough for training the neural network. The problem is that with so few samples, the neural network will "memorize" the training set. Memorization of the training set renders the network unable to perform well on inputs that were not part of the training set. To circumvent this problem, additional training samples are generated. For each NOS depth sounding the closest AVIRIS pixel and each of its eight neighboring pixels are extracted for use as training data. This procedure does introduce some misregistration between depth and radiance values. However, the spatial misregistration is small (20m) and can be tolerated since the nine-fold increase in training set size eliminates the memorization problem. The resulting expanded training set is made up of 2340 samples, and the test set contains 66 samples.

The neural network used with both data sets consists of four layers of neurons. The input layer contains 39 nodes. Two hidden layers contain 20 and 10 neurons, respectively. The output layer contains a single neuron. The logarithm of the depth is used in the neural network rather than depth. The logarithmic conversion is done to emphasize accuracy at shallow depths, which are of primary Navy interest.

Before processing the data for both areas, a nautical chart was digitized and control points were handpicked between the AVIRIS image and the chart. The image was then warped to the chart allowing AVIRIS sample and line coordinates to be related to latitude and longitude.

## 4. RESULTS

The RMS test set error between the neural net estimated depth and the NOS sounding for Tampa Bay is 3.9 ft over the 0 to 30 ft range. The RMS error computed for only those points of less than 10 ft depth (the range of greatest Navy interest) is 2.7 ft. Figure 4 is a scatterplot of the NOS depth versus the neural network estimated depth with the zero error line denoted. The Tampa Bay results may be more accurate than these statistics indicate. This is possible because of the age of the NOS soundings which are from 1953 and 1954. The mouth of Tampa Bay is a very dynamic region with shoals that migrate constantly in response to storm and tidal forcing. A certain, but unknown, amount of the reported errors in hyperspectral depth retrieval must certainly be attributable to errors resulting from outdated ground truth. Figure 5 shows the depth image that results from applying the trained neural network to a full AVIRIS scene. The image is contoured by depth for comparison with nautical chart depths.

The test set RMS error for the Santa Rosa Sound is 3.0 ft over the range 0 to 28 ft. The RMS error computed for only those points less than 10 ft. depth is 1.9 ft. Again the problem of outdated ground truth occurs. Half of the NOS data for the Santa Rosa Sound are from 1934 and 1935 with the other half from 1985 and 1986. Figure 6 shows a scatterplot of the NOS depth versus the neural network estimated depth with the zero error line denoted. Figure 7 shows the neural network resultant depth image with contours.

The fact that the method gave similar results in atmospherically corrected and uncorrected data is of interest. It appears that if one wants to map spectral radiance in the ocean/atmosphere system to water depth by supervised training methods, it may often be possible to do that using observations at the top of the atmosphere rather than

observations corrected to the surface of the water. The main need for atmospheric corrections would be to apply a network trained on one data set to a second data set without retraining.

The AVIRIS spectra seemed to separate into two distinct clusters when grouped by depth (Figure 8). This grouping is believed to represent two bottom types, presumably white sand and a lower reflectance bottom such as mud or vegetation. However, no bottom-type ground truth has been compared with this classification. By choosing a depth dependent threshold on channel 20, the clusters could be seperated to produce a bottom type classification for depths up to 9 ft. The low reflectance and high reflectance bottom classifications for Tampa Bay are delineated in Figure 9. In conversations with other researchers, this bottom-type distribution seems to be consistent with general knowledge of Tampa Bay. Figure 10 shows a bottom-type classification for Santa Rosa Sound that is produced by similar thresholding methods. In Figures 9 and 10, the high reflectance bottom is represented as white, the low reflectance bottom as green, and blue represents depths > 9 ft where the bottom is not classified.

## 5. CONCLUSIONS

This study shows that neural networks can be used to establish a mapping of water color into depth. Since the mapping is done by training the neural network, atmospherically uncorrected data can be used. Working with uncorrected data carries the implicit assumption of horizontal homogeneity of the atmosphere in the study area. The accuracy of the method is not established with certainty because the depth ground truth certainly has significant errors of unknown magnitude. The method does not assume a uniform bottom-type. In fact, the data sets analysized show evidence of differing bottom types, which allow for simple bottom-type classification.

## 6. FUTURE PLANS

The important question for operational implementation of hyperspectral bathymetry is the universal nature of the spectral radiance to water depth mapping. If the network must be totally retrained for each data set, the operational utility of the method is reduced. The universality question is currently being investigated.

In order to address the impact of old ground truth on the error statistics, the Naval Research Laboratory (NRL) has recently collected bathymetric data sets at Kaneohe Bay, Hawaii and Camp Pendleton, California. This will allow the method described here to be applied in an area with more current, research-grade ground truth.

Continuing work includes combining AVIRIS bands to simulate SeaWiFS and Landsat data to determine the potential for useful bathymetric work by applying similar techniques to these other platforms.

## 7. ACKNOWLEDGMENTS

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2. G. Vane, R.O. Green, T.G. Chrien, H.T. Enmark, E.G. Hansen, and W.M. Porter. 1993. "The Airborne Visible/Infrared Imaging Spectrometer (AVIRIS)," Remote Sens. Environ. 44:127-143.

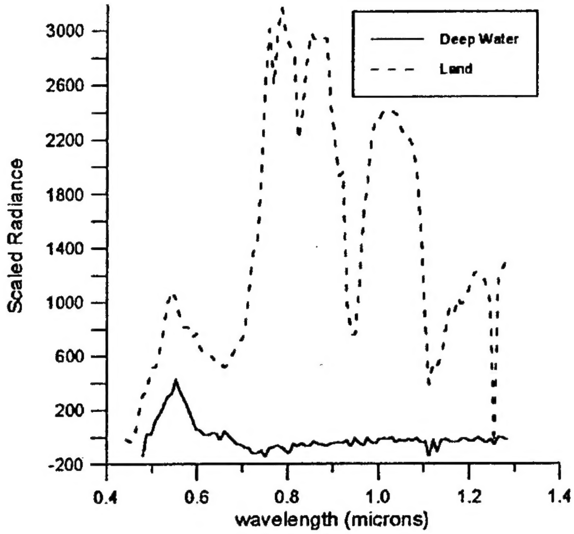


Figure 1. Typical Land and Water Spectra Recorded by AVIRIS in Tampa Bay

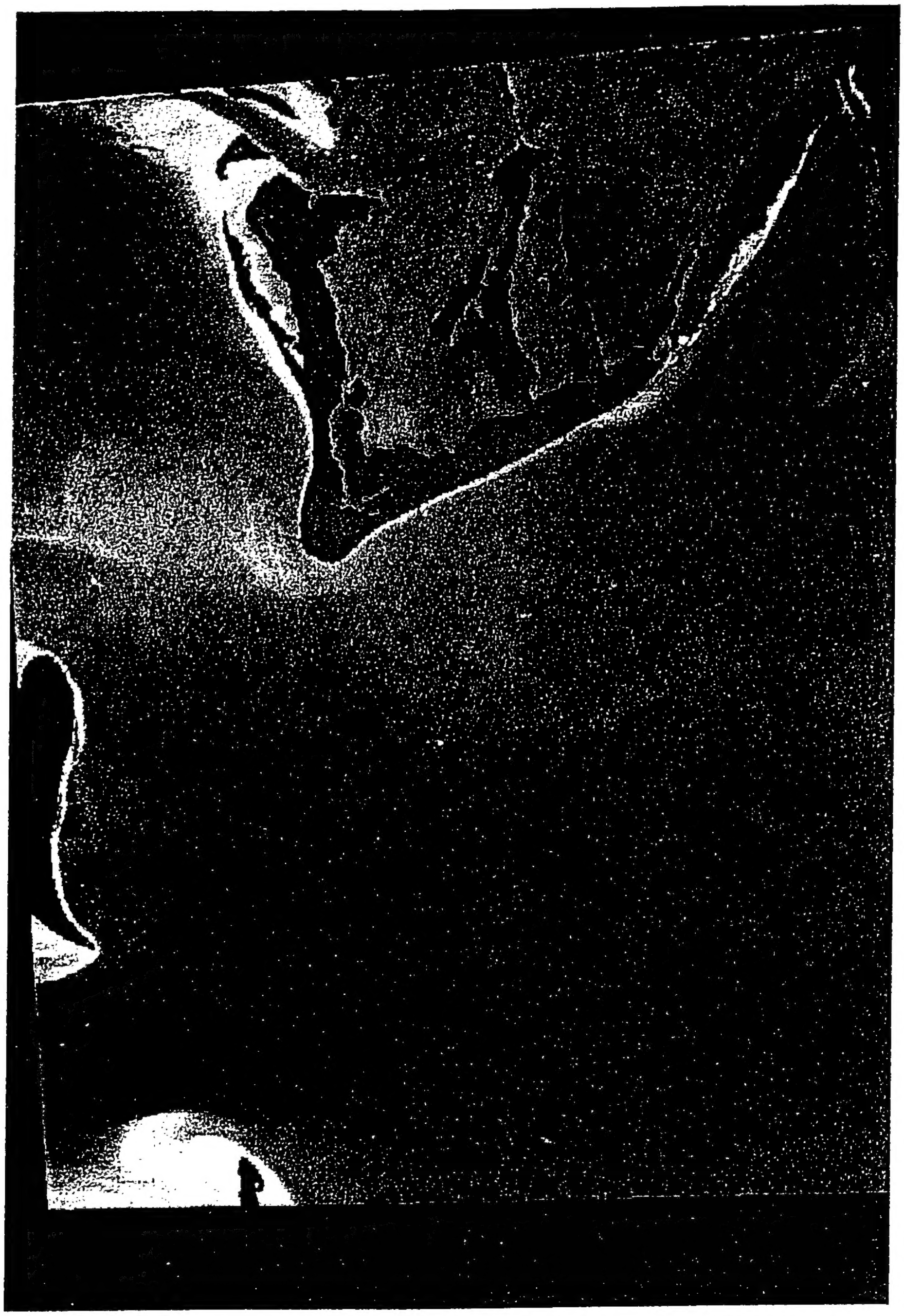

Figure 2. AVIRIS Image of Tampa Bay

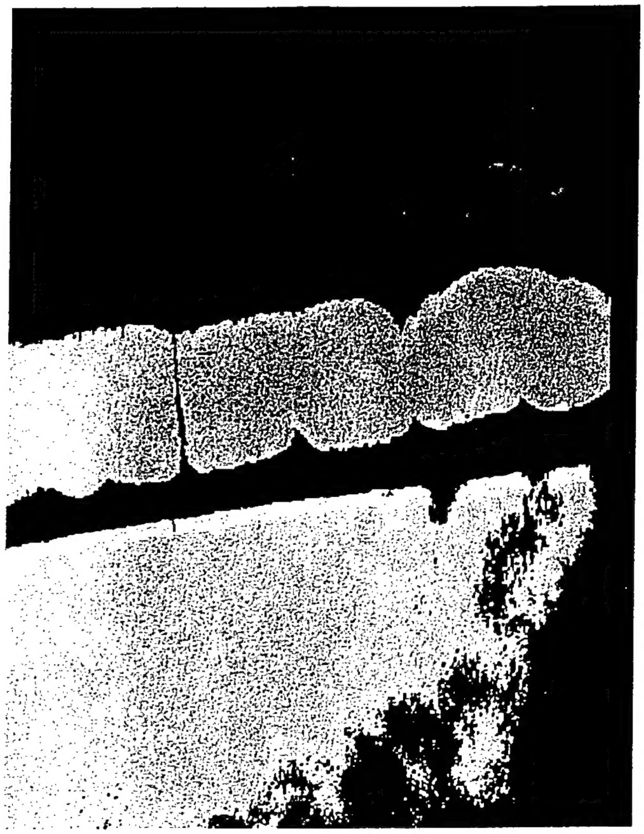

Figure 3. AVIRIS Image of Santa Rosa Sound

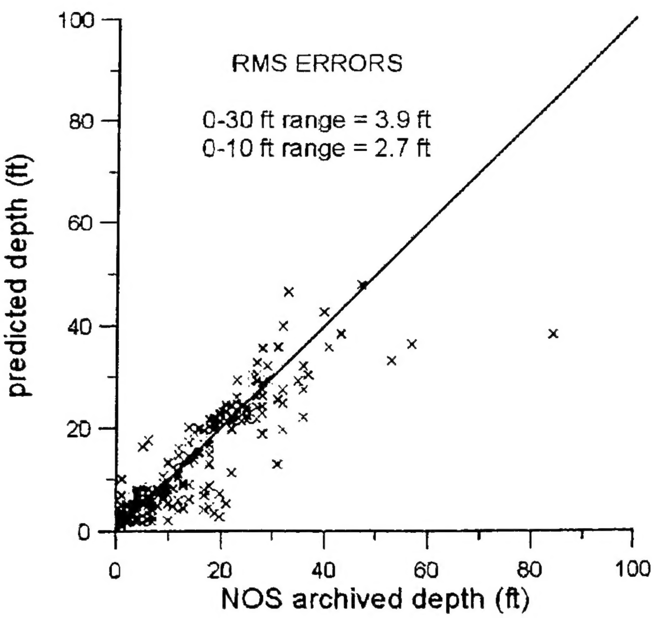


Figure 4. Test Set Error Distribution for Tampa Bay

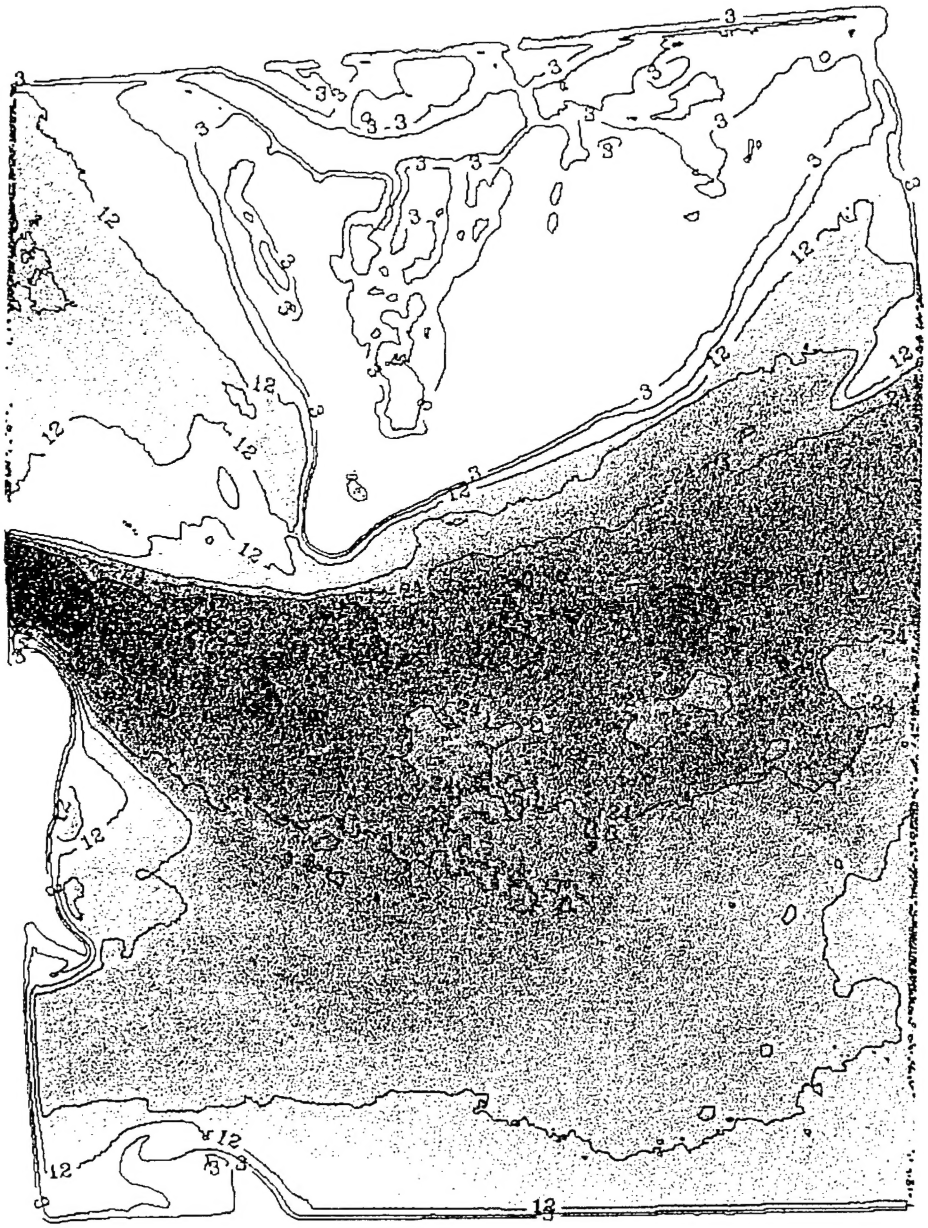

Figure 5. Gray-Scale Encoded Depth Map fro Neural Network

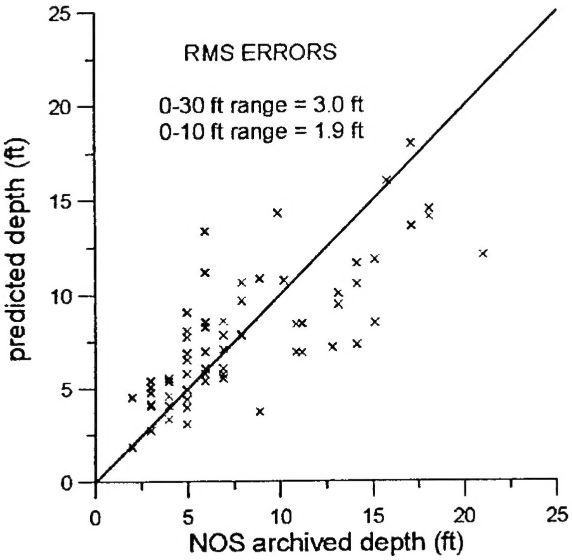


Figure 6. Test Set Error Distribution for Santa Rosa Sound

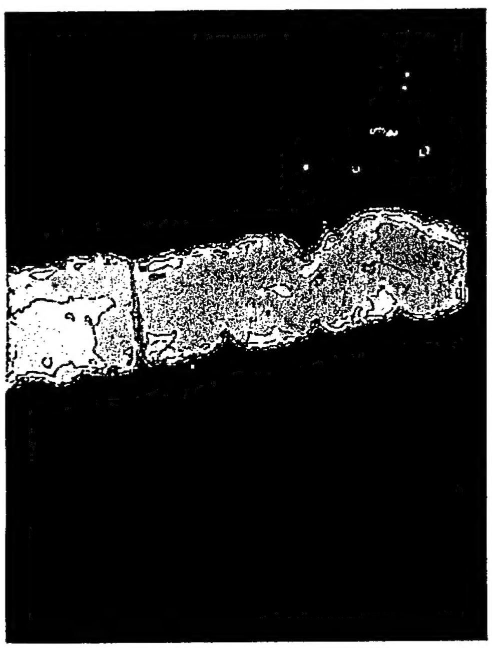

Figure 7. Gray-Scale Encoded Depth Map from Neural Network

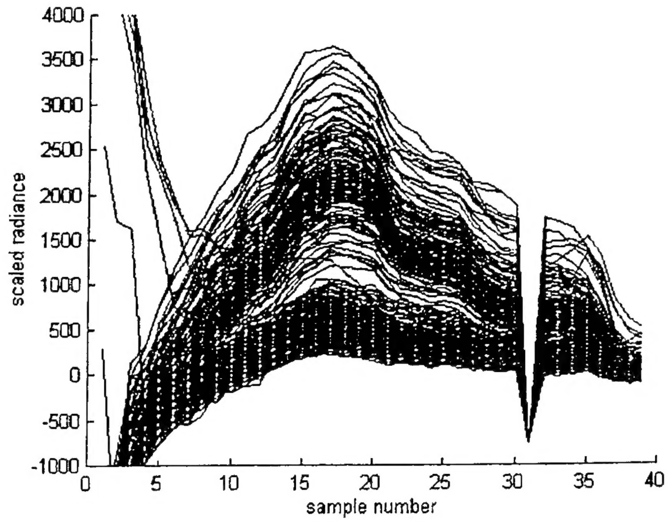


Figure 8. Spectra from Ground Truth Points with Depths < 3 ft for Tampa Bay

Figure 9. Tampa Bay Bottom Type Classification

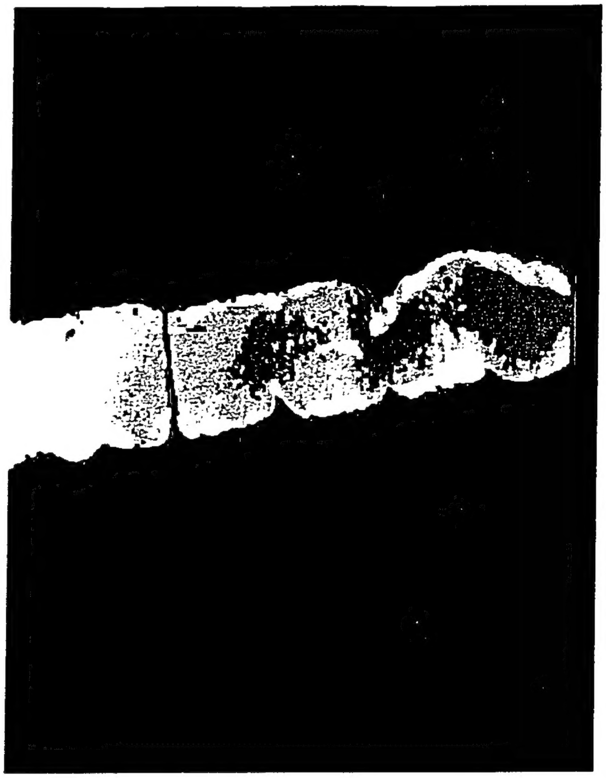

Figure 10. Santa Rosa Sound Bottom Type Classification